

Tourism Industry Specialization, Overtourism, and Community Resilience: A Spatial Path Analysis Approach

Eunjung Yang
University of Florida

Jinwon Kim
University of Florida

Follow this and additional works at: <https://scholarworks.umass.edu/ttra>

Yang, Eunjung and Kim, Jinwon, "Tourism Industry Specialization, Overtourism, and Community Resilience: A Spatial Path Analysis Approach" (2021). *Travel and Tourism Research Association: Advancing Tourism Research Globally*. 16.
https://scholarworks.umass.edu/ttra/2021/research_papers/16

This Event is brought to you for free and open access by ScholarWorks@UMass Amherst. It has been accepted for inclusion in Travel and Tourism Research Association: Advancing Tourism Research Globally by an authorized administrator of ScholarWorks@UMass Amherst. For more information, please contact scholarworks@library.umass.edu.

Tourism Industry Specialization, Overtourism, and Community Resilience: A Spatial Path Analysis Approach

1. Introduction

Community resilience to disasters is defined as a community's ability to successfully respond to disasters before, during, and after they occur, ultimately decreasing current and future disaster impacts (Cutter, Ash, & Emrich, 2014). As damage from disasters critically threatens community sustainability, many scholars and practitioners have tried to enhance community resilience (Cutter & Derakhshan, 2020). Recently, the economic impacts of tourism have been highlighted in community resilience literature as they directly support the recovery stage after disasters (Lee, Kim, Jang, Ash, & Yang, 2020; Romão, 2020). Beyond economic effects, tourism has also been a key factor enhancing community capital (Guo, Zhang, Zhang, & Zheng, 2018) and infrastructure (Powell et al., 2018), both of which form community resilience. As a result, previous studies have typically examined the positive role of tourism in enhancing community resilience by (a) measuring the relationship between tourism industries and community resilience (Mazzola, Pizzuto, & Ruggieri, 2019; Psycharis et al., 2014) and (b) developing a community resilience framework that shows how tourism links to community resilience (Bec, McLenna, & Moyle, 2016; Lew, 2014). These studies have ultimately proved that tourism enables communities to build adaptive responses to natural hazards (Tsai, Wu, Wall, & Linliu, 2016).

However, as one recent Florida case study (Lee et al., 2020) found spatially positive and negative effects of tourism industries on economic resilience, consideration of spatially varying tourism effects has also become important. These mixed results could be associated with overtourism (Dodds & Butler, 2019). Although tourism industry specialization can bring economic benefits to communities, the overgrowth of tourism industries can also negatively

affect environmental carrying capacity, including pollution and excessive resource use, leading to the possibility of spatially mixed relationships (Dodds & Butler, 2019). Nevertheless, based on our knowledge, no empirical research has been conducted to examine spatially positive and/or negative relationships between tourism industry specialization and community resilience and a factor causing these mixed relationships. This lack of model/framework testing, which can suggest guidelines for effective resilience management strategies, is an ongoing limitation for resilience research in the tourism field (Ritchie & Jiang, 2019).

Accordingly, this study aims to (a) explore the spatially heterogeneous mixed relationships between tourism industry specialization and community resilience and (b) examine the moderating effect of overtourism on their mixed relationships. Geographically weighted regression (GWR) combined with spatial path analysis, which has rarely been used in previous tourism literature, was applied to case studies of 3,108 counties in the United States (U.S.) and 67 counties in Florida. Based on prior studies, environmental pollution, which can reflect overtourism, was used as a key moderator (Tsai et al., 2016). The findings will support community practitioners and tourism policymakers in building localized sustainable resilience enhancement strategies by cooperating with tourism industries.

2. Methodology

Fig. 1 shows the proposed model to investigate the moderating effects of overtourism on the relationship between tourism industry specialization and community resilience. Fig. 2 shows a methodological flowchart for GWR and spatial path analyses.

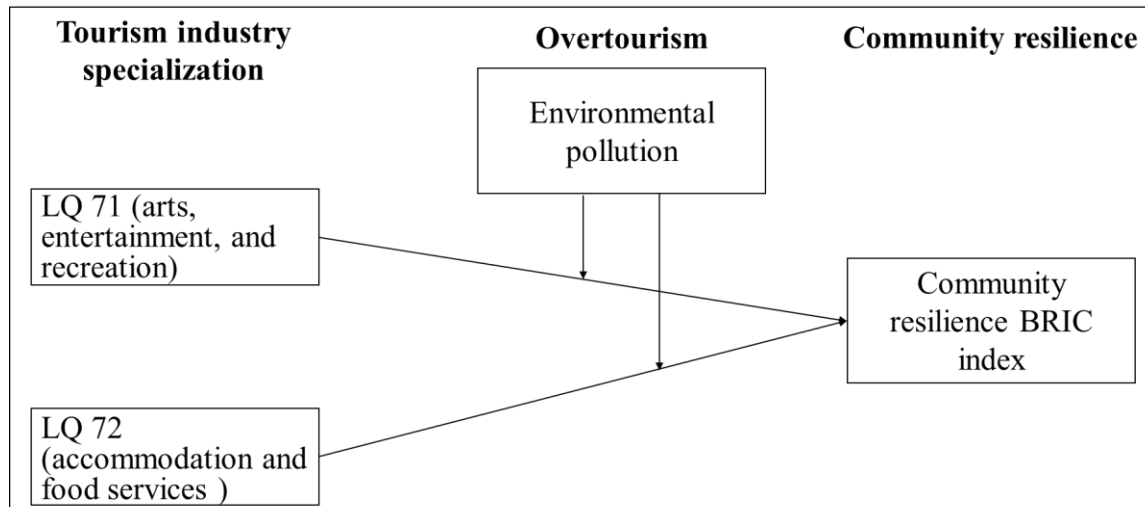


Fig. 1. The proposed model.

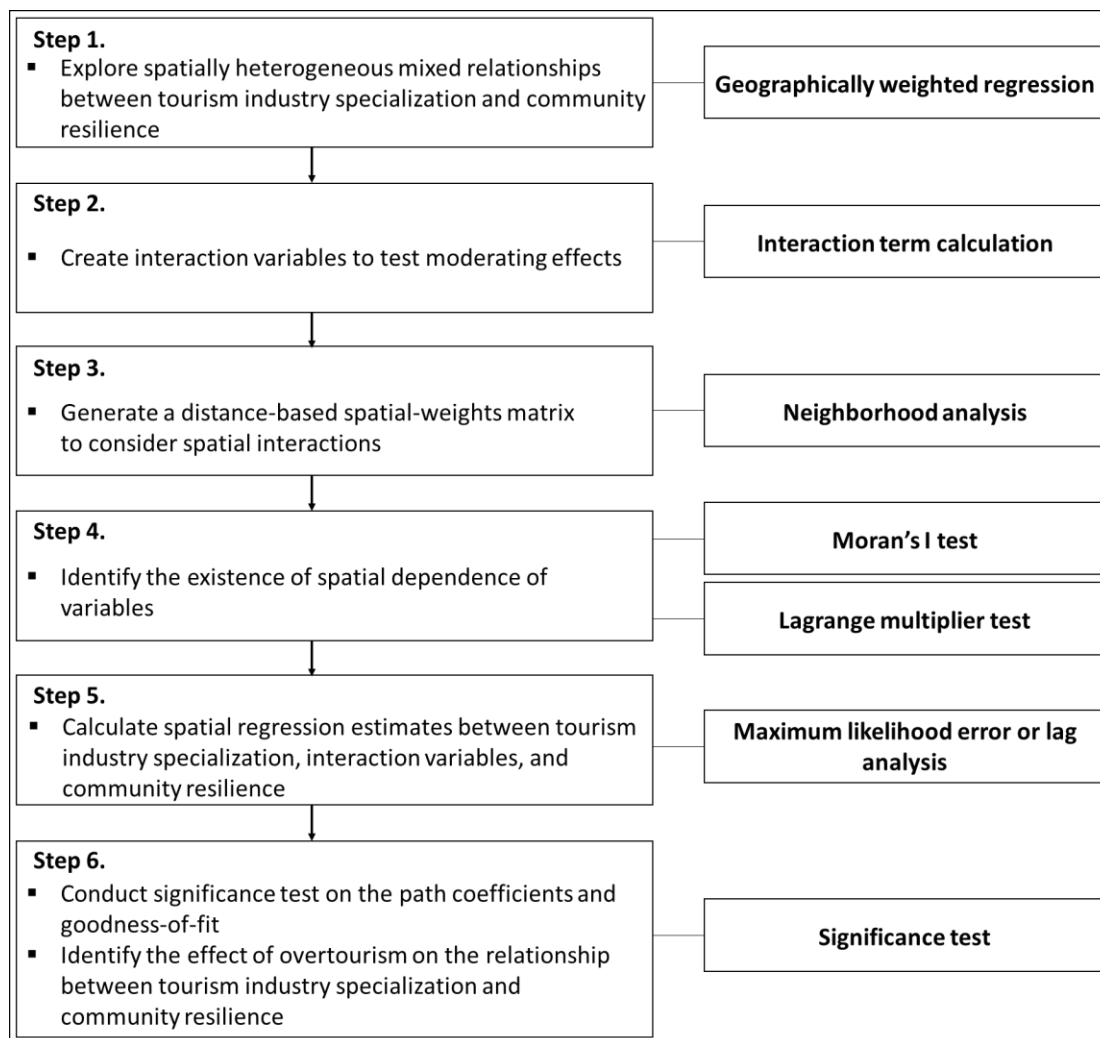


Fig. 2. A methodological flowchart.

Step 1 aimed to explore spatially heterogeneous mixed relationships between tourism industry specialization and community resilience. Tourism industries were categorized into (a) arts/entertainment/recreation and (b) accommodation/food services, based on the North American Industry Classification System (NAICS) codes. The degree of tourism industry specialization was represented by location quotient (LQ) values (Sohn, 2013). The LQ shows the relative concentration of each industry in a community compared to the average in the U.S. (Lee et al., 2020). This study calculated the averages of the 5-year (2011-2015) LQ values to match the measurement period of Cutter and Derakhshan's (2020) 2015 community resilience metrics. Community resilience metrics were based on Cutter et al.'s (2014) Baseline Resilience Indicators for Communities (BRIC) approach. GWR, which can construct a local specific spatial regression equation for each county, was applied to understand the spatial variability between tourism industry specialization and community resilience. The proposed GWR model is as follows:

$$R_p = \beta_{p0}(X_p, Y_p) + \beta_{pt}(X_p, Y_p)T_{pt} + \varepsilon_p$$

where R_p is the community resilience score of county p ; (X_p, Y_p) refers to the latitude and longitude of county p 's centroid, respectively; β_{pt} is the local regression coefficient for tourism sector t of county p ; and ε_p is the error term at county p .

Steps 2-6 involved investigating the moderating effects of overtourism on the relationship between tourism industry specialization and community resilience. Moderating effects were examined via spatial path analysis proposed by Sulistyo, Subanar, and Pulungan (2018). Spatial path analysis considers spatial dependency, which is the degree of spatial autocorrelation between variables, assuming that “everything is related to everything else, but near things are more related than distant things” (Tobler, 1970, p. 236). Addressing spatial dependency increases model accuracy when variables are spatially correlated (Sulistyo et al.,

2018). Since spatially referenced (i.e., county-based) tourism industry specialization, overtourism, and community resilience variables have spatial dependency, their relationships must be investigated by considering spatial dependency.

In step 2, interaction variables (environmental pollution*each tourism industry specialization) were generated as the outcome of the mean-centered predictors. The variable—environmental pollution (the log-transformed 5-year [2011–2015] average on-road CO₂ emissions per capita per county)—was used to represent overtourism, a moderating factor (Tsai et al., 2016). In step 3, distance-based spatial weight matrices at the U.S. and Florida levels were created to consider spatial interactions. In step 4, spatial dependency was tested using Moran's I and a Lagrange multiplier. In step 5, moderating effects were examined using a maximum likelihood (ML) spatial lag/error approach, which can control spatial effects. In this study, ML spatial error estimation was selected since spatial error models showed better model performance than spatial lag models. The proposed ML spatial error model is as follows:

$$\vec{D} = b + \vec{c}I + \vec{r}; \quad \vec{r} = \lambda S_w \vec{r} + \xi$$

where \vec{D} is the dependent variable; b is the intercept term; \vec{c} is a regression coefficient; I is a set of explanatory variables; λ represents a spatial error coefficient; S_w represents a distance-based spatial weight matrix; \vec{r} represents the residual vector; and ξ is the modified error term. In step 6, model significance tests on the path coefficients and goodness-of-fit were conducted. All data sources and operational definitions of variables used in this study are summarized in Table 1.

Table 1

Variables for analysis

Variable	Operational definition (unit: county)	Literature	Source
Community resilience	The 2015 overall BRIC score of community resilience	Cutter et al. (2014)	HVRI
LQ71	The 5-year (2011-2015) average LQ of arts/entertainment/recreation	Lee et al. (2020)	DEP
LQ72	The 5-year (2011-2015) average LQ of accommodation/food services		
Environmental pollution	The log-transformed 5-year (2011-2015) average on-road CO ₂ emissions per capita	Gately et al. (2019)	DARTE

Note: BRIC: baseline resilience indicators for communities; DARTE: Database of Road Transportation Emissions; DEP: Department of Economic Opportunity; HVRI: Hazards & Vulnerability Research Institute; LQ: location quotient.

3. Results and Discussion

Figs. 3–4 and Table 2 summarize the results of the GWR models. The results show various spectra of GWR-based local coefficients ranging from negative to positive, indicating that all tourism sectors have spatially varying mixed relationships with community resilience in the U.S. and Florida. For the U.S. models, LQs71–72 are positively associated with community resilience based on the mean values of local coefficients, but they are also negatively associated with community resilience based on the minimum local coefficients (Fig. 3). These results indicate that, in general, all tourism sectors may support enhancing community resilience, but tourism sectors have a negative effect on community resilience in certain counties in the U.S., suggesting spatially heterogeneous mixed effects of tourism sectors on community resilience. Similar to the U.S. case, tourism sectors and community resilience in Florida have spatially varying mixed relationships, as shown in Fig. 4. However, unlike the relationships at the U.S. level, based on the average local coefficients, LQ71 is positively associated with community resilience, but LQ72 is negatively associated with community resilience in Florida, indicating

that LQ72 has stronger potential to negatively affect community resilience in Florida, a tourism-dependent state. The GWR results can be explained by the concepts of spatial conditionality and heterogeneity because each community is structured differently due to the uneven distribution of resources and human activities, which may influence unique industry development (Kim, Kim, & Jang, 2021). Thus, the effects of tourism on community resilience may differ by community and type of tourism sector.

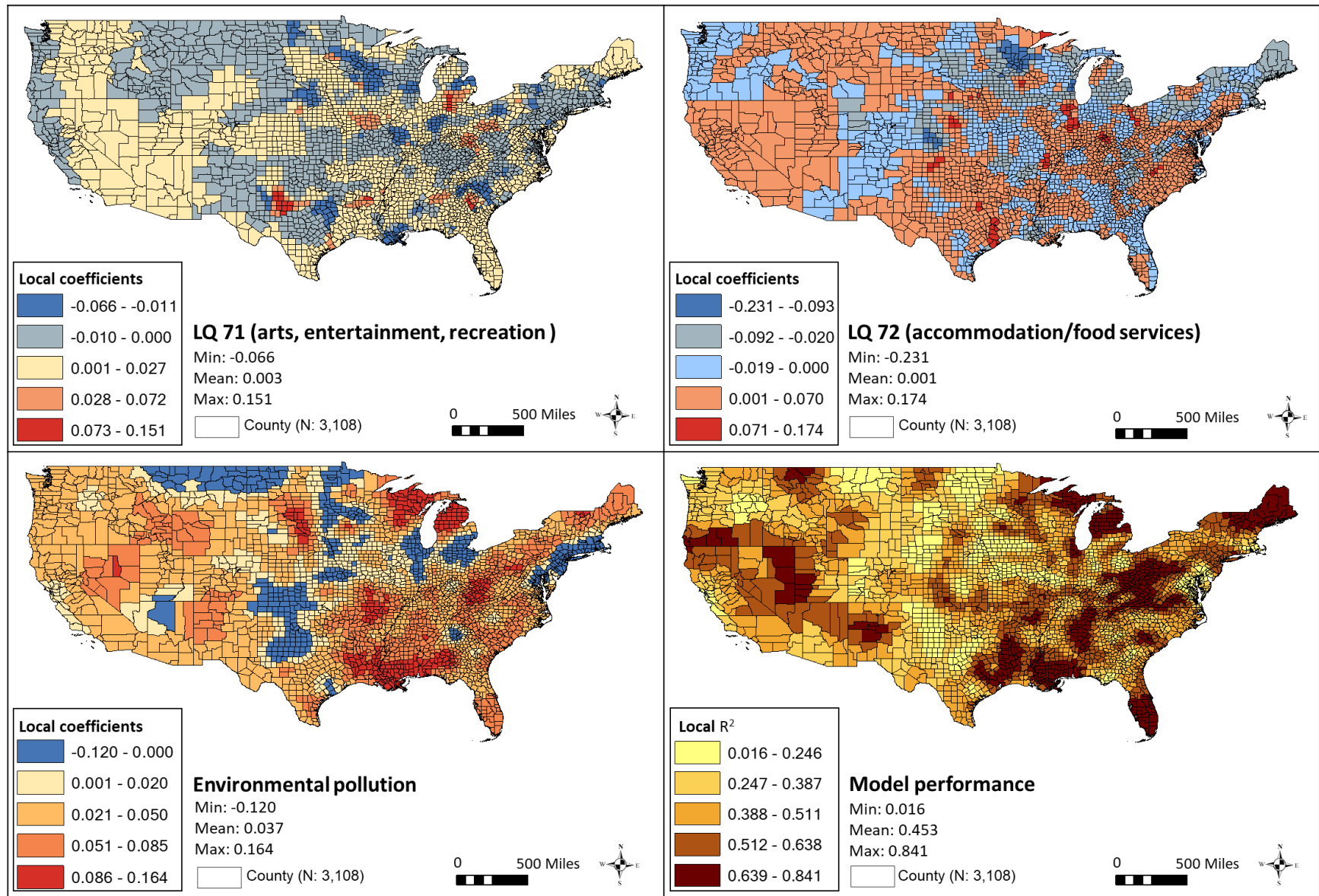


Fig. 3. GWR results (U.S. model)

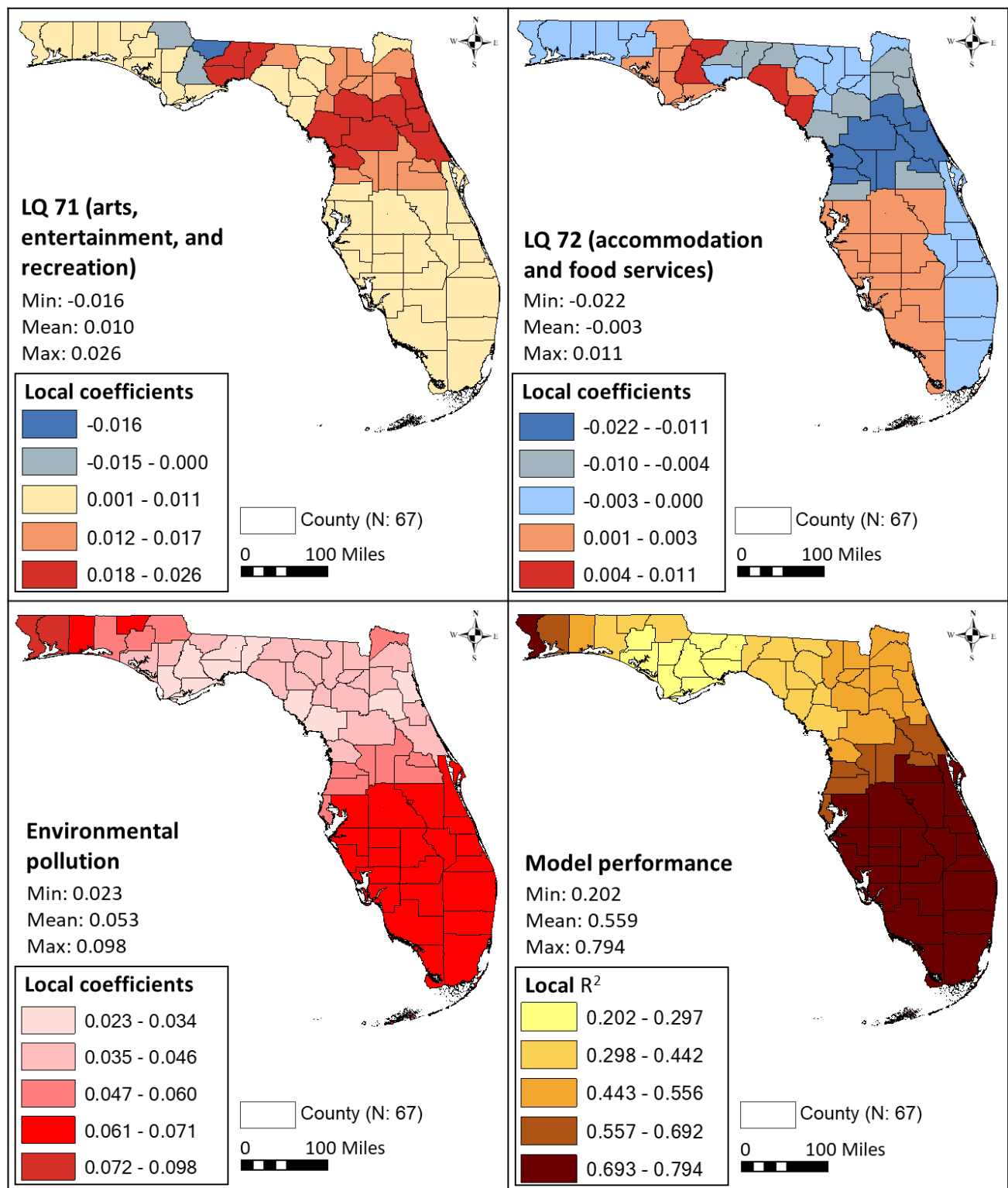


Fig. 4. GWR results (Florida model).

Table 2

Results of the GWR model

Variable	United States			Florida		
	GWR coefficient			GWR coefficient		
	Min.	Mean	Max.	Min.	Mean	Max.
Intercept	0.728	2.303	4.166	1.451	1.951	2.377
LQ71	-0.066	0.003	0.151	-0.016	0.010	0.026
LQ72	-0.231	0.001	0.174	-0.022	-0.003	0.011
Environmental pollution	-0.120	0.037	0.164	0.023	0.053	0.098
Local R ²	0.016	0.453	0.841	0.202	0.559	0.794
Adjusted R ²		0.626			0.515	
AIC _c		-6653.964			-144.811	

Note: AIC_c: corrected Akaike's information criterion; LQ: location quotient.

After exploring spatially heterogeneous mixed relationships between tourism industry specialization and community resilience, the moderating role of overtourism on their relationships was examined. Before conducting the spatial path analysis, this study conducted Moran's I test to identify the existence of spatial dependence, which is an essential precondition for conducting a spatial path analysis (Sulistyo et al., 2018). By using ordinary least squares (OLS) regression residuals, we found statistically significant spatial dependences at the U.S. level (Moran's Index: .522, $p < .001$) and the Florida level (Moran's Index: .484, $p < .001$). Fig. 5 and Table 3 summarize the results of the spatial path analysis based on the spatial error model estimation. In the U.S., LQs71–72 significantly and positively affect community resilience ($B = .0014$, $p = < .05$; $B = .0061$, $p = < .05$, respectively). Environmental pollution negatively moderates the relationships between (a) community resilience and LQ71 and (b) community resilience and LQ72, but environmental pollution has a statistically significant impact on the relationship between community resilience and LQ71 ($B = -.0003$, $p = < .05$). In Florida, LQs71–72 significantly and positively affect community resilience ($B = .0117$, $p = < .01$; $B = .0071$, $p = < .05$, respectively). Environmental pollution negatively moderates the relationships between (a)

community resilience and LQ71 and (b) community resilience and LQ72, but environmental pollution has a statistically significant impact on the relationship between community resilience and LQ72 ($B = -.0130$, $p = <.05$). In terms of the model diagnostics, spatial path models at both the U.S. and Florida levels performed better than the OLS models based on their higher R^2 and log likelihood and lower AIC and Schwarz criterion (see Table 3).

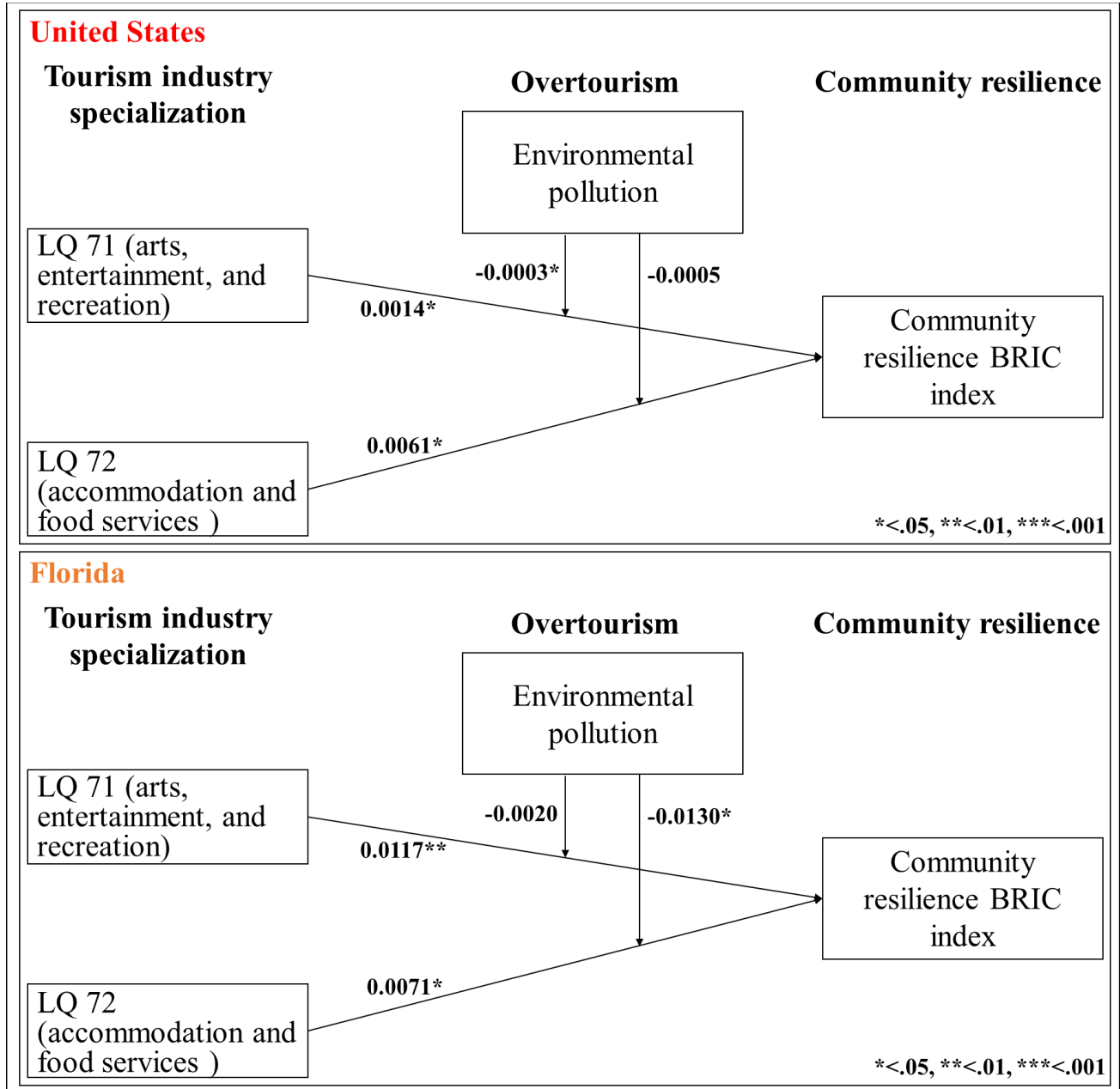


Fig. 5. The results of spatial path analysis.

Table 3

Results of the spatial path model based on the spatial error model estimation

Path	United States			Florida		
	OLS	GWR		OLS	GWR	
	β	β	p	β	β	p
Constant	2.7318	2.7147	0.00	2.6014	2.6149	0.00
LQ71 → Community resilience	-0.0007	0.0014	0.03	0.0106	0.0117	0.00
LQ72 → Community resilience	0.0030	0.0061	0.03	0.0079	0.0071	0.01
Environmental pollution → Relationship (LQ71→Community resilience)	2.1972	-0.0003	0.02	0.0097	-0.0020	0.97
Environmental pollution → Relationship (LQ72→Community resilience)	-0.0003	-0.0005	0.13	-0.0190	-0.0130	0.01
Lambda		0.9179	0.00		0.5415	0.00
R ²	0.00	0.58		0.32	0.57	
Log likelihood	1656.99	2885.45		68.74	79.64	
Schwarz criterion	-3273.76	-5730.70		-116.46	-138.27	
AIC	-3303.97	-5760.91		-127.48	-149.29	

Note: AIC: Akaike's information criterion; LQ: location quotient.

The results could be explained as follows. Although tourism industry specialization has the potential to enhance community resilience (Tsai et al., 2016), overtourism can exceed the carrying capacity of a community, which in turn can negatively affect community resilience (Dodds & Butler, 2019). In other words, certain levels of tourism industry specialization may positively affect specific aspects of carrying capacity, including economic carrying capacity (e.g., high income levels), resulting in enhanced community resilience. However, the negative effects of overtourism (e.g., environmental pollution) might exceed the positive effects of tourism industry specialization in certain counties, leading to decreased community resilience. Interestingly, when comparing moderating effects at the U.S. and Florida levels, LQs71–72 have a more positive effect on community resilience in Florida, and environmental pollution more strongly moderates the relationship between tourism industry specialization and community resilience (see Fig. 5). This means that tourism sectors have a stronger effect on community resilience in tourism-dependent communities than in other communities in general. Additionally,

overtourism may be the key moderating factor that more strongly affects the relationship between accommodation/food service specialization and community resilience in tourism-dependent communities.

4. Conclusion and Implications

This is the first exploratory study to examine the moderating effect of overtourism that significantly influences the spatially heterogeneous mixed relationships between tourism industry specialization and community resilience in the U.S. and Florida. Theoretically, this study widens the scope of community resilience research by examining spatially heterogeneous mixed effects of tourism on community resilience. Prior studies have focused more on the positive effect of tourism on community resilience without considering moderating factors and spatial dependence, both of which can explain the mixed effects of tourism on community resilience. By adapting GWR and spatial path analyses, this study shows that the spatially heterogeneous relationships between tourism industry specialization and community resilience may be positive or negative depending on (a) overtourism, (b) the characteristics of communities, and (c) the tourism sector types across counties in the U.S. and in Florida. Specifically, overtourism significantly and negatively affects the relationships between community resilience and the accommodation/food service tourism sectors in Florida, which is a tourism-dependent state. However, in general, overtourism significantly and negatively affects the relationships between community resilience and the tourism sectors of arts/entertainment/recreation in the U.S. These findings widen prior studies' findings that tourism can enhance community resilience by identifying the role of overtourism and comparing the effects of tourism sectors across communities.

From the community policy perspective, the findings show that policymakers need to invigorate tourism industries to improve community resilience by developing an action plan to relieve the negative effect of overtourism. Specifically, tourism-dependent counties, which have abundant accommodations and food services, should be aware of the negative effect of overtourism. As the effects of tourism sectors and overtourism vary according to communities, the findings of this study help policymakers better understand how to establish effective localized action plans for enhanced community resilience by considering the effect of overtourism and the spatially varying effects of tourism industry specialization on community resilience.

References

- Bec, A., McLennan, C. L., & Moyle, B. D. (2016). Community resilience to long-term tourism decline and rejuvenation: a literature review and conceptual model. *Current Issues in Tourism, 19*(5), 431–457.
- Cutter, S. L., Ash, K. D., & Emrich, C. T. (2014). The geographies of community disaster resilience. *Global Environmental Change, 29*, 65–77.
- Cutter, S. L., & Derakhshan, S. (2020). Temporal and spatial change in disaster resilience in US counties, 2010–2015. *Environmental Hazards, 19*(1), 10–29.
- Dodds, R., & Butler, R. (2019). The phenomena of overtourism: A review. *International Journal of Tourism Cities, 5*(4), 519–528.
- Farrell, B. H., & Twining-Ward, L. (2004). Reconceptualizing tourism. *Annals of Tourism Research, 31*(2), 274–295.
- Guo, Y., Zhang, J., Zhang, Y., & Zheng, C. (2018). Examining the relationship between social capital and community residents' perceived resilience in tourism destinations. *Journal of Sustainable Tourism, 26*(6), 973–986.
- Lee, Y.-J. A., Kim, J., Jang, S., Ash, K., & Yang, E. (2020). Tourism and economic resilience. *Annals of Tourism Research, 103*024.
- Lew, A. A. (2014). Scale, change and resilience in community tourism planning. *Tourism Geographies, 16*(1), 14–22.
- Mazzola, F., Pizzuto, P., & Ruggieri, G. (2019). The role of tourism in island economic growth and resilience: A panel analysis for the European Mediterranean countries (2000–2015). *Journal of Economic Studies, 46*(7), 1418–1436.
- Powell, R. B., Green, T. F., Holladay, P. J., Krafte, K. E., Duda, M., Nguyen, M. T., ... Das, P.

- (2018). Examining community resilience to assist in sustainable tourism development planning in Dong Van Karst Plateau Geopark, Vietnam. *Tourism Planning and Development*, 15(4), 436–457.
- Psycharis, Y., Kallioras, D., & Pantazis, P. (2014). Economic crisis and regional resilience: detecting the ‘geographical footprint’ of economic crisis in Greece. *Regional Science Policy & Practice*, 6(2), 121–141.
- Ritchie, B. W., & Jiang, Y. (2019). A review of research on tourism risk, crisis and disaster management: Launching the annals of tourism research curated collection on tourism risk, crisis and disaster management. *Annals of Tourism Research*, 79, 102812.
- Romão, J. (2020). Tourism, smart specialisation, growth, and resilience. *Annals of Tourism Research*, 84, 102995.
- Sohn, J. (2013). A quantitative analysis of the spatial agglomeration pattern among the Korean cities. *The Korean Geographical Society*, 48(1), 56–71.
- Sulistyo, W., Subanar, & Pulungan, R. (2018). Development of a spatial path-analysis method for spatial data analysis. *International Journal of Electrical and Computer Engineering*, 8(4), 2456–2467.
- Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, 46, 234.
- Tsai, C.-H., Wu, T. (emily), Wall, G., & Linliu, S.-C. (2016). Perceptions of tourism impacts and community resilience to natural disasters. *Tourism Geographies*, 18(2), 152–173.